# Aircraft loads assessment and its effect on aircraft structure – machine learning approach

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The development of modern air-vehicles is a harmonized activity of numerous disciplines, such as aerodynamic sciences, propulsion, materials science, structural analysis, systems, avionics, manufacturing and more. The airframe design is based on data provided from these disciplines (for example, updated loads, weight, mass distributions and more). These data are usually provided to the designer in predetermined milestones that are correlated to logistic considerations (such as manufacturing preparations or purchasing of long lead items), all in light of the expected entry to market date.

In today competitive market of commercial aircraft, the entry to market date is extremely important. To meet such an aggressive deadline, the design drawings may be released prior to completion of structural substantiation for the most updated external loads. If the mature loads loops are issued relatively late in the development phase, there is a great risk that retrofits in structural parts that were already manufactured will be required. Such retrofits impact the program schedule and related costs. To overcome this difficulty, it is highly important that the stress engineer will be able to assess the external loads loops upon their issuance, so unnecessary retrofits or redesigns of structural parts can be prevented.

The structural substantiation process is described in Figure 1. The failure criteria are chosen with respect to a given structural detail, and margins of safety are obtained as the ratio $F_{all}/F_{app} - 1$, with $F_{all}$ and $F_{app}$ are the allowed and applied loads, respectively. In large scale development programs with thousands of external load cases, revised stress analyses upon issuance of new external loads is a time-consuming process that can easily last several months. As explained above, such delay in stress substantiations may have a significant impact on the program costs and timeline.

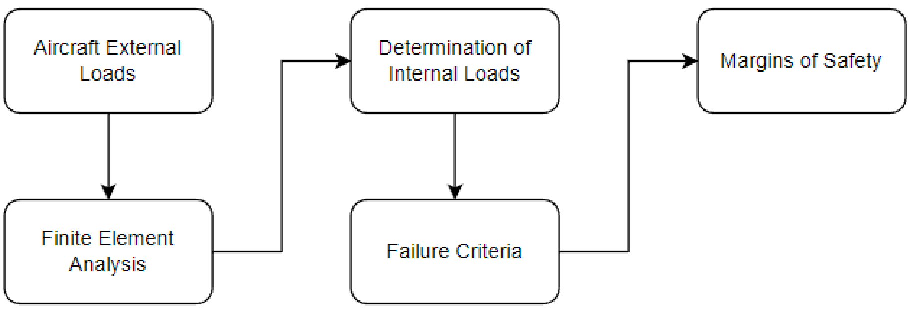



**Figure 1: Top level structural substantiation flowchart**

The current study proposes a change in the paradigm of how structural details are substantiated. To this end, machine learning strategies are used to significantly enhance the analysis duration, thus providing an assessment tool for the stress engineer to evaluate the expected impact of a new load loop on the existing design of the structural detail. The new approach, which is based on machine learning regressions, is presented in Figure 2.

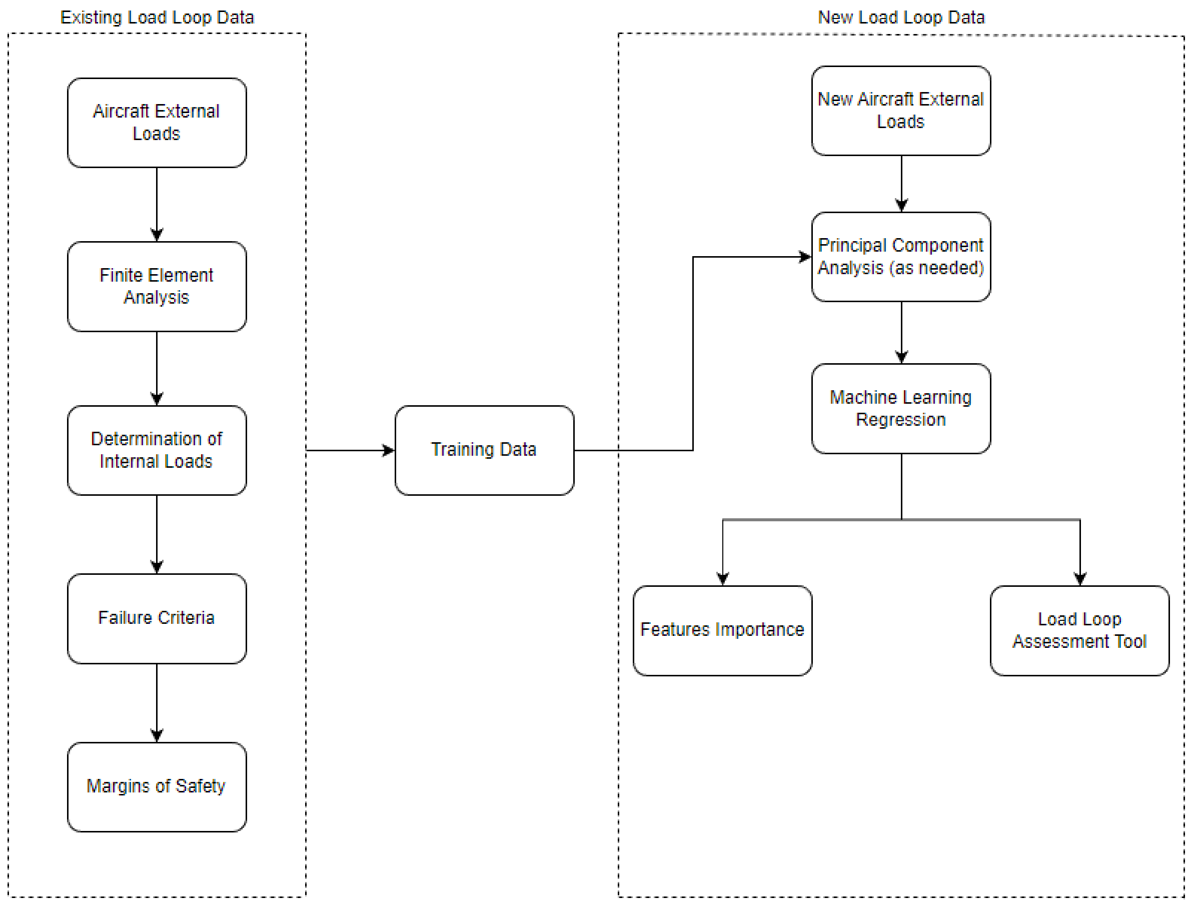



**Figure 2: Proposed process for new loads loop assessment**

The main idea underpinned by the flowchart presented in Figure 2 is to establish relations between the external loads and the margins of safeties in structural details of concern. This process can be ideally performed analytically in cases when the finite element model and failure criteria are linear. If not, machine learning approaches can be used to establish such relations. Once the algorithm is trained based on the previous external loads loop, predictions of the expected margins of safety can be made for a given new set of external loads using regression. If needed, principal component analysis can be performed to reduce the number of features used for regression. Two outputs are plotted, predictions of the expected margins of safety and evaluation of features importance. Understanding the effect of each feature (i.e., external load component at specific location) is an important tool to support engineering judgement regarding the expected effect of the new loads set on the current design.

Machine learning strategies are used in recent years to address complex technological problems in the field of structural analysis [1] - [7]. The main advantage of such approaches is their capability to efficiently perform regressions for a given dataset with capability of dealing with large database that includes multiple features.

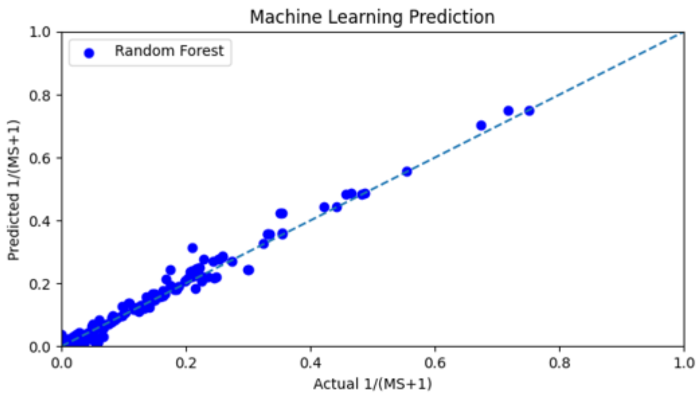
In this study, the Multilayer Perceptron Neural Network (MLP) and the Random Forest (RF) methods were used. According to the MLP approach, the different features characterizing the problem investigated are represented as neurons with given weights. These weight functions are coefficients that construct the output signal using summation. An activation process is employed throughout this procedure that maps the summed weights input into the output of the neuron.

Each layer in this algorithm includes a row of neurons, and one network may include several layers. The first layer (the 'visible layer'), represents the input data. The layers after the input layer are the 'hidden layers' since they are a combination of the input layer with their corresponding weights. The final layer is the 'output layer'; The obtained output vector is compared to the training data, and a cost function is obtained. The cost function is minimized by a back-propagation process that optimize the different weight coefficients throughout this process.

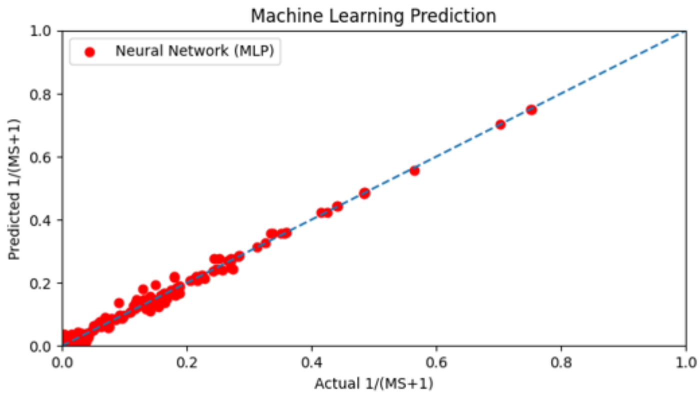
Random Forest (RF) is based on a set of simple random decision trees that are executed in parallel with no mutual interactions. The RF algorithm constructs the outcome of these decision trees and outputs the average (mean) of all individual predictions. Each initial tree includes only a portion of the input features, and with parallel calculations of these decision trees, the regression process becomes very efficient. This parallel aggregation of the decision trees outputs is called bagging (Bootstrap Aggregation).

The process described in Figure 2 was investigated. To this end, a structural detail that is subjected to 17 load components, with 67 load cases was chosen. 37 critical locations were identified in this structural detail, and margins of safeties were obtained for each of the 67 load cases studied. The data collected construct a large training database of nearly 2,500 data points. 90% of this dataset was used for training, with 10% used for validation.

Figure **3** present the accuracy of the machine learning predictions versus the actual margins of safety. The comparison is normalized as 1/(MS+1), with MS denotes the margin of safety, so that both axes vary between 0 and unity for a positive margin of safety. As can be seen from the graphs presented in this figure, an excellent agreement between predictions and actual margins of safety is achieved, even for relatively small training dataset (recall that the training data includes only 67 load cases; it is expected that larger number of load cases used for training will significantly improve the predictions). The neural network algorithm was found to be superior with respect to the random forest.




(a)




(b)

**Figure 3: Predictions vs. actual margins of safeties for the validation data. (a) Random Forest and (b) Neural Network**

Finally, demonstration of the importance of each individual feature with respect to the obtained margin of safety is presented in Figure 4. Three critical locations are presented, and the components identified as critical were validated via classical stress calculation of the structural detail. Such identification of the importance of each load component is highly important to support engineering judgement that is commonly used for evaluation of new load set.

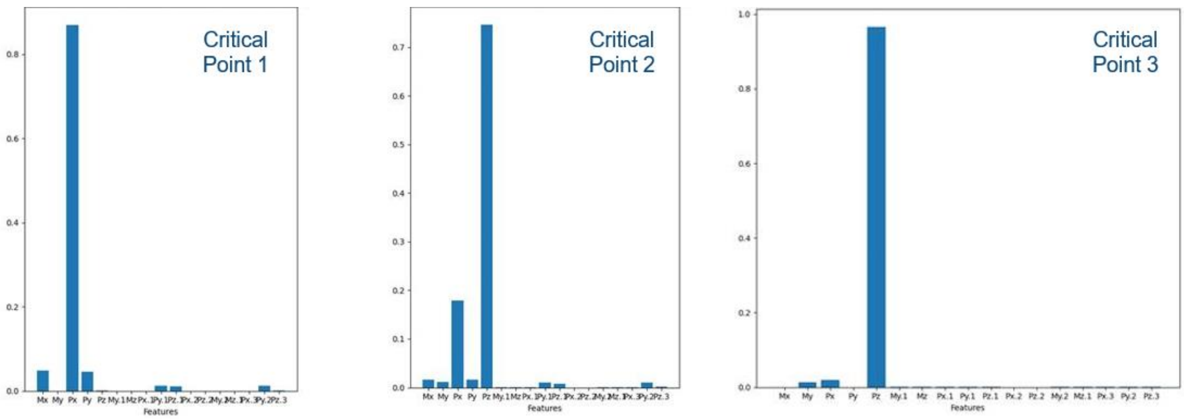



**Figure 4: An example of features importance at three critical location**

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